Riemannian Score-Based Generative Modeling

Abstract

Score-based generative models (SGMs) are a powerful class of generative models that exhibit remarkable empirical performance. Score-based generative modelling (SGM) consists of a ``noising'' stage, whereby a diffusion is used to gradually add Gaussian noise to data, and a generative model, which entails a ``denoising'' process defined by approximating the time-reversal of the diffusion. Existing SGMs assume that data is supported on a Euclidean space, i.e. a manifold with flat geometry. In many domains such as robotics, geoscience or protein modelling, data is often naturally described by distributions living on Riemannian manifolds and current SGM techniques are not appropriate. We introduce here Riemannian Score-based Generative Models (RSGMs), a class of generative models extending SGMs to Riemannian manifolds. We demonstrate our approach on a variety of manifolds, and in particular with earth and climate science spherical data.